Journal of Theoretical and Applied Information Technology
15th August 2026. Vol.104. No.15

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

BIOFUSION-YOLO: AN INTELLIGENT DEEP LEARNING FRAMEWORK FOR MORPHOLOGICAL AND COLOR-BASED DETECTION OF NUTRIENT DEFICIENCIES IN BANANA LEAVES

N. LAKSHMI KALYANI [1], KOLLA BHANU PRAKASH [2*]

[1] Research Scholar, Department of CSE, K.L. Deemed to be University, Green Fields, Vaddeswaram-522302, Guntur District, A.P, India.

[2*] Professor, Department of CSE, K.L. Deemed to be University, Green Fields, Vaddeswaram-522302, Guntur District, A.P, India

[1] nlakshmikalyani268@gmail.com , [1] neerukondait@gmail.com , [2*] drkbp@kluniversity.in

ABSTRACT

Properly diagnosing nutrient deficiencies in the crop is essential in order to maximize fertilizer use, improve agricultural productivity and to sustain farming. Most of these methods used for soil nutrient assessment (primarily chemical laboratory-based) are more time consuming, expensive, and can't be conducted real-time. This paper proposes a new method named MorpBioFusion-YOLO that addresses these problems using the morphological and color-based deep learning in RGB images obtained by the field. To achieve this, we have proposed a novel method, called MorpBioFusion-YOLO, which at the same time tackles the problem of autonomous classification of nutrient deficiency, based on the deep learning in both morphological and color components from RGB images captured in the field. The suggested framework includes feature extraction at multiple scales, adaptive morphological representation learning using colour-sensitized spatial analysis functions to find nutrient stress pattern of Boron, Calcium, Iron, Magnesium, Manganese, Zinc, Potassium, Sulphur deficiency and Healthy leaf conditions. From a technical perspective, it predominantly uses an adapted detection backbone composed of YOLO and allows for a path aggregation system that performs detailed fusion operations in the various features, notwithstanding varying illumination, orientation and background conditions across the entire image. Augmentation strategies and texture preserving transformations are employed during training to increase the ability of generalization. Our proposed model performance on the banana nutrient deficiency plants with labels yields high overall mean Average Precision (mAP@0.5): 81.7% with the extreme accuracy in identifying Healthy and Sulphur classes 0.995 and good performance in other classes as Boron deficiency, Potassium deficiency and Manganese deficiency. Moreover, the presented framework is able to provide effective real-time inference performance, ideal for edge-supported smart farming applications. Experimental studies showed that morphological structures of leaves, venation characteristics, chlorosis pattern and variation in the level of pigmentation are reliable traits for the estimation of nutrient stress. The proposed BioFusion-YOLO framework is intelligent agricultural solution for realizing early nutrient diagnosis and precision crop management that is effective, low in cost and scalable.

Keywords: *Precision Agriculture, Nutrient Deficiency Detection, Banana Leaf Analysis, Morphological Feature Fusion, Explainable Deep Learning, RGB Plant Phenotyping, Multi-Scale Object Detection, Smart Farming, Leaf Color Analysis, Agricultural Computer Vision and Edge AI in Agriculture*

1. INTRODUCTION

Demands for research grew for productivity and environmentally-friendly, low-cost nutrient use and management has never been more important. Changes in soil nutrient levels are critical since they significantly affect both plant growth, the yield of the crop and soils and agriculture sustainability. The nutrient estimations methods used in the conventional soil and/or leaf analysis are very time-consuming methods, which require an expensive analyzer or trained manpower for a lab analysis. Biochemically they can be confirmed by these processes, but the process can't be well tracked down in an under-resourced and a

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

developing farmland situation. Therefore, the demand for nutrient deficiency detection systems for precision agriculture or intelligent farming applications which are low-cost, on-line and non-destructive increases[1].

The symptoms of nutrient stress are directly associated with the pigment in the leaves where the stress is observed as chlorosis and necrosis, general leaf morphology stress and leaf marginal scorching and tree shoot stress / die-back; these symptoms can be used as natural resources to detect nutrient stress. Relatively low levels of B, K, Ca, S, Mg, Fe, Zn and Mn lead to specific symptoms which can be detected by the use of digital imaging techniques. The agricultural productivity has been mainly developed into complicated visual pattern recently, which allows visual developmental process to be automated and has greatly improved the efficiency of the process. Convolutional Networks and Object detection frameworks have proven to be an outstanding solution to detect very subtle difference in leaf texture, color gradient, leaf structural differences under different environmental stresses [7]. The major problem with most of the suggested techniques, however, is that they are unable to deal with generalization, multiple scale and high illumination and orientation variability, and discrimination between similar nutrient classes. There has been considerable interest in nutrient stress analysis techniques which can be performed in the shortest time possible without destructive chemical analysis, using images. From the point of view of the usage of an edge device, it is particularly attractive to use RGB imaging system for Agro application as the RGB imaging systems are economy and edge device friendly based on the agriculture application. Both of the nutrient stress symptoms are quite similar, though, and may be hard to tell apart from the nutrient deficient symptoms. For instance, the symptoms of the deficiency in Calcium, Magnesium and Zinc are actually comparable -- this is actually why it really would be challenging to be able to differentiate classes. Moreover, the automatic nutrition recognition is complicated by lighting (ie. lighting condition), background noise and such factors as occlusion, as well as the variability in leaf orientation. Current machine learning (ML) [37] solutions have not, however, addressed the need for capturing un-symptomatic areas and morphology context, and actually have worked out to make the detection less reliable in the field[2].

To overcome these gaps, this paper concentrated on proposing a novel approach, called “BioFusion-YOLO” by morphological and color-aware deep learning from RGB images captured in the field for the goal of explaining the nutrient deficient banana leaf detection, which was called the “Biological Fusion Prediction”. In view of the aforementioned deficiencies this paper aimed to propose an alternative approach by morphological deep learning and colour-aware deep learning from RGB images taken in the field, termed “BioFusion-YOLO”, for detecting the banana plant's nutrient deficiency in plant leaves “BioFusion Prediction”. The proposed architecture incorporates the advanced YOLO detection backbone – designed with the spatial Pyramid Pooling and Path Aggregation mechanism, which can be effectively exploited to leverage spatial information and to derive comprehensive context for the above end. Furthermore, the work is adapted to enrich the texture techniques to guarantee a better generalisation in different production environments that are exposed the farms. Characteristics such as venation features and areas of fineness Cale, pigmentation variation and chlorosis have been intentionally retained as discriminative and as relevant to stress and/or as a mark of nutrient stress. The evaluation of the proposed system is done through experiments which show that the system is able to detect strong performance with an overall mAP@0.5 of 81.7% profiting from the efficient real-time inference for precision farming[3] and edge enabled agricultural monitoring system.

This work makes important contributions as follows:

1. This paper proposes the Morphological-based deep learning system and Color-aware based deep learning system on the banana leaves to detect the nutrient deficiency.
2. The novel designed architecture for robust nutrient stress identification is an architecture based on YOLO frame, multiple scale context fusion and biologically inspired feature learning framework.
3. The first processing procedures proposed are to minimize the difference in natural environments and illumination, together with texture preserving are recommended.
4. The fine grain texture representation, as well as the proposed morphological context analysis (for representing the global level) can be applied effectively for the identification of the same problem in both cases (i.e. nutrient deficiency with similar appearance).
5. With the completion of different experiments, it is proved that good detection results are obtained and it can be applied in

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

real time in the intelligent precision agriculture system.

In Section 2 a literature review is done and the existing approaches for nutrient deficiency detection based on images, deep learning approaches and phenotyping of agriculture sectors are discussed. The framework proposed here (BioFusion-YOLO) is detailed in Section 3 which consists of the morphological and colour-aware detection architecture, the feature extraction methodology and the adaptive feature augmentation pipeline and training methodology. Section 4 expands on some of the methods used to prepare the data set, how the model is set up, and a description of the experimental set-up and metrics used to test the models generated. The Precision–Recall analysis, F1–Confidence analysis, Matrix of misclassification and comparison to the baseline models are involved in discussing the obtained results of experiments in section 5. Finally, Section 6 provides a brief summary of this paper along with future directions in the field of multispectral image processing, incorporation of Explainable Artificial Intelligence and Generalized Nutrient Stress Analysis for multiple varieties.

2. BACKGROUND WORK

In recent years, images have been a recent field of study in plant analysis of nutrient deficiencies since it is a fast, non-destructive and economical way to monitor crops while investigating its nutrition in the field of precision agriculture. The time consuming, costly and impractical soil and nutrient analyses like the traditional methods also cannot be applied in agriculture on a large scale and real-time. This has been made possible through advances in artificial intelligence technologies like computer vision and deep learning, but also through the inclusion of several hyper-spectral imaging and explainable AI systems capable of automatically identifying nutrient stress from the plant's leaves, thanks to its involvement in different morphological, pigmentation, venation and spectral plant responses. Within this, the special is Banana beans as the lack of a balance nutrient has a great impact on the quality of the fruit, but on the crop yield and susceptibility to the tree disease.

Recent research has been directed at making innovative deep learning architectures for nutrients stress detection based on leaf imagery. Sunil et al. [1] proposed a nutrient deficiency score estimation system based on deep learning with multi-scale adaptive feature pooling with banana plants for the identification of the nutrient deficiency in the plant. They have managed to incorporate chlorosis related properties from local areas and global features on which the classifiers have performed better than the different nutrient classes. This however was something of an inexpensive utilization of resources and a reason was not available to be explained about the use of agriculture in practice in this model. Also, Muthusamy and Ramu [2] have explored an efficient neural architecture search (NAS) for a light-weight approach towards characterizing the nutrient deficiency and severity of crop leaves. The CPU ability to classification, however, demonstrated under different environmental conditions showed that the framework has good capability to classify; yet, the framework could be generalized under the situation of the field, which was different from the situation studied.

Graph-based agricultural intelligence systems have recently become a focus of great attention, too. Bera et al. [3] has proposed an approach that is based on the graph convolution network (GCN) to detect plant nutrition deficiency and disease. On complex agriculture data set, they discovered that their model worked well in keeping the spatial relation between features and enhancing the quality of the classification. However the models are made in a graph and feature engineering can be complex and time-consuming in preparing for deployment in large-scale. There is another research Wu et al. [4] used Modified segmentation model of leaves with Multispectral imaging (MS) to detect the deficiency of nutrients. They have successfully supported their work in the discrimination work when compared to the conventional RGB imaging techniques. Another drawback of multi-spectral imaging systems is that they are very expensive and not widely available, especially in a resource limited farm environment.

A further key focus of Deep Learning systems for 'Precision Agerade' is the need to have richly scalable, light weight, open and understandable agricultural intelligence systems. Chettri et al. [5] conducted a systematic review on the applications of deep learning in precision agriculture in solving some of the challenges they highlighted: Multiple datasets paradigm, environment uncertainty, machine learning interpretability issues, and models application in real agriculture production systems limitations. This review identified the importance of incorporating deploying BS, computational efficient and scalable systems in various conditions.

The latest methodologies with interest for detecting nutrient stress are the machine vision and handmade image processing. Min, X [6] comprehensively reviewed the different techniques used to detect nutrient deficiencies in plants via

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

proximal imaging, machine learning techniques and concluded that traditional morphological or color features are valuable phenotypic indicators of plant nutrient stress. But such traditional composition and manufacturing methods cannot still distinguish the nonlinear relationship of features in the different environmental conditions. While image-driven diagnosis was subsequently used for the detection of plant diseases with the help of CNNs for the first time by Mohanty SP [7] paved the way to the application of deep CNN in agriculture. Most of the early solutions that have achieved these are very accurate, but lack localization capabilities, and are unsuitable for deployment in a real field environment.

The concept that emerged was limiting the use of the RGB imaging and morphological analysis to detection of specific nutrients and only a few studies have been published. The deficiency state of N, P and K in rice crop can be detected by Xuxiang Ta et al. (2017) proposed hierarchical image analysis method [8] that is based on static scanning technology. They tried to assess their work using the colour and textural quality of leaves that reacts to various lights and alterations in the light. Furthermore, this was expanded by Cen, H et al., [9] to the rice leaves, and in terms of their dynamic morphology and colour response to the environment of nutrients stress. The correlation between the nutritional disorder and temporal colour change was good and the moralization deformation was very close to the correlation of colour change with time.

The capacity for the estimation of nutrients has been enhanced also by the use of newly developed nutrient indices in the visible spectrum. The morphological parameters and visible-light vegetation indexes were used to assess the N content in potato plants by Fan Y et al. [10]. The correlation between the chlorophyll index and nutrient level was good. Similarly Kior et al. [11] presented an overview of the RGB Imaging techniques for remote sensing of plants properties and discussed its usage in precision agriculture with a low-cost imaging system.

This is the issue with classification of data for nutrient deficiency – there's no solution, it's awesome to see all this success by using a deep neural network! They used deep neural network to learn the feature by itself and classify the nutrient deficiency in rice plants yielded good classification accuracy like Bera, A. et al. [12] using image of leaves. Later, Bardhan et al [13] introduced a deep neural network architecture based on deep ensemble named “IncepV3Dense” for classification of micro nutrient deficiency in Banana crop which is more robust in coping with the changes in the Banana field condition. However the models can be quite complex, and in ensemble structures further complicate and increase the overhead.

Availability of datasets has also played a crucial role in developing the research of deep learning in agriculture. Sunitha et al. [14] employed a completely labeled banana leaf nutrient deficient dataset, but the present study is different as multiple nutrient deficient dataset of macro and micro nutrients were used. They played an important role in the development of supervised deep learning in the analysis of nutrients in bananas. But, the Plant nutrient Deficiency/Plant Disease classification proposed by P. N. Shendage et al. [15] that relied on graph convolution attracted the interest of learning spatial features work for agriculture image analysis.

The significance of Agricultural Decision Support Systems (ADSS) in the era of Insightfulness and Explainable AI (XAI) is emerging as a crucial aspect. In terms of interpretability and potential of CNN based nutrient deficiency identification systems, Nikitha, S. et al. [16] found the systems to be potentially fruitful but reliant on the ease of understanding by the trustworthy agricultural AI system to find success. Ensemble machine learning algorithms have been shown to attain accuracy in predicting the diabetes at an early stage as mentioned by Gayathri et al. [17] that combining different algorithms can be used to make accurate predictions. The range of applicability of the use of computational intelligence techniques in identification of health-related patterns in data is much wider as was pointed out in the work presented. These results further confirm the viability of using advanced learning frameworks for early detection tasks, and motivated the use of the advanced learning framework for the task of detecting nutrient stress in agriculture, which was explored in this study.

In addition, traditional methods for image analysis have also been used for detecting nutrient stress research on nutrients. This method has been applied successfully firstly in the image processing technique along with histogram for nutrient management of maize and proved as effective by using texture-based analysis of nutrient in maize successfully (Li, Y., Gerdessen [18]). Some works resorted to back-propagation neural networks to estimate other nutrient requirements according to the leaf colour [19] and estimate soil nutrient based on hyperspectral remote sensing and computer vision models [20].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Advanced Multimodal Agricultural Sensing (MAS) systems has also broadened the range of nutrients that are being monitored. In their point cloud analysis and nutrition monitoring via neural networks by J. Clave [21] they pay attention to the combination of colour and structure information of lettuce. To get the species level identification capability of a crop, Urfan et al. [22] proposed a deep hierarchical features extraction method-based DL-CRoP platform. Unhealthy leaf characteristics estimation which is proposed by Buakum, B. et al. in [23] is a two-stage algorithm, but is capable of confirming the capability of the plant health monitoring by the structural feature of the plant.

The methods of approach nutrient estimation due to fusion and optimization have been attempted by a number of studies. In the real environment, S. B. Sulistyo et al. [24] created an algorithm to perform this estimation more robustly, by implementing the estimation with a neural network fusion (NNF) followed by optimizing the estimation algorithm by using genetic algorithm optimization. The effectiveness of machine vision techniques that are used to evaluate changes in leaf pigmentation for varying nitrogen levels of apple trees was investigated by A. Paudel et al. [25] and relations between the change of various colour parameters and N level were established.

Over the last few years, with the development of deep learning, amazing results and highly scalable and lightweight models in the agricultural domain have been achieved, making its application readily available. Besides, in the field of agriculture, deep learning is growing towards the direction of "explainable models" and "light models", which seems to be convenient to use. Adaptive light weight neural architecture search (ALAS) approach to classify the nutrient deficiency of bananas is proposed by Muthusamy et al. [26] which utilizes ensemble optimization method, in their developed approach, in the attention layer. The growing needs for transparency among deep-learning models [34] are particularly prominent in the field of agriculture, as they are becoming more and more intelligent. In agriculture, development of models with deep learning focus has been given on transparency as a key element and to manufacture intelligent agriculture systems, such as the G. Loganathan et al. [27] intelligence system, show especial emphasis in this field. In their review of the different approaches of deep learning applied in plant disease classification A. Aissaoui et al. [28] have extensively explored the complex issues due to multi-scale representation of features and robustness of environment.

Also the attention of the biologically-informed and rule-guided learning models has shifted towards the context of nutrient stress analysis. Mondal et al. [29] had a similar idea to integrate the knowledge that is available in the agricultural domain with the deep learning models and predict the onset of nutrient deficiency to a crop at an early stage with the help of domain guided neural network. However, to identify the similar nutrient deficiency within this group of similar appearances, K. A. M. Han et al. [30] developed plant nutrition deficiency feature pooling methods which were suitable in multi-scale identification of the nutrient deficiency in banana.

The latter trend – that of deep learning using everywhere in agricultural intelligence systems – is evident in the reviews of this kind that exceed in size. Pacal, I et al. [31] presented review of deep learning techniques for plant diseases under variable climates, imbalanced data sets and the interpretability problems deep learning techniques have with plant nutrition disease identification. M. Koca et al. [32] and Shoaib M et al. [33] investigated the newest architectures of deep learning systems in a different application which involves classifying plant disease and nutrient analysis, respectively and concluded the need of models that can be easily deployed in real time and lightweight systems.

There are possibilities for good research too on MSI and some optimum segmentation on nutrient stress analysis. Optimized segmentation developed by Z. Y. Poh et al. [35] was combined to the multispectral imaging system to enhance the ability of discrimination nutrient deficiency. The plant disease classification methods based on deep learning is introduced by L. Ale et al. [36] that concentrates on solving problem and its applicability in real time system usage. Finally, the authors provide an overview on the potential practical applications in agriculture for a nutrient deficiency detection task, benefiting from the combination of morphological analysis, multiscale feature fusion, explainable AI and the incorporation of nutrient responsive Deep learning techniques.

Although great strides have been made, there are still a number of gaps in research. This alleviates the problems, but current models are rarely highly transferable to other light and field conditions, difficult to explain, and not capable of distinguishing between similar (and indistinguishable) nutrient deficiencies patterns of Calcium stress, Magnesium stress and Zinc stress. Besides, an extensive number of methods exist which are relying on information retrieved from the spectrum that do not rely on recognized morphology or utilizes contextual information based on the learning of textures which are aware of colors. The constraints present an opportunity to introduce the proposed BioFusion-YOLO framework which can be assisted by adaptive multi-scale feature extraction and morphological representation learning, and fusion of context information for nutrient deficiency recognition in banana leaves.

3. PROPOSED BIOFUSION-YOLO FRAMEWORK

The proposed framework in this paper, namely, BioFusion-YOLO is explained in this section. The proposed system is an intelligent nutrient deficiency detection system for a banana plant leaf using morphology and colour with special designing for a real field environment. The proposed system is feature representation learning based-in biological approach and accurate multi-scale object detection system of the nutrient-stress pattern accurately associated with each nutrient stress condition and the healthy leaf state of Boron, Calcium, Iron, Magnesium, Manganese, Zinc, Potassium, Sulphur deficiency and healthy leaf state. The overall framework consists out four main components: (i) Destruction detection architecture: morphological and color-aware; (ii) The augmentation pipeline: biologically-inspired; (iii) The training and deployment strategy: optimized.

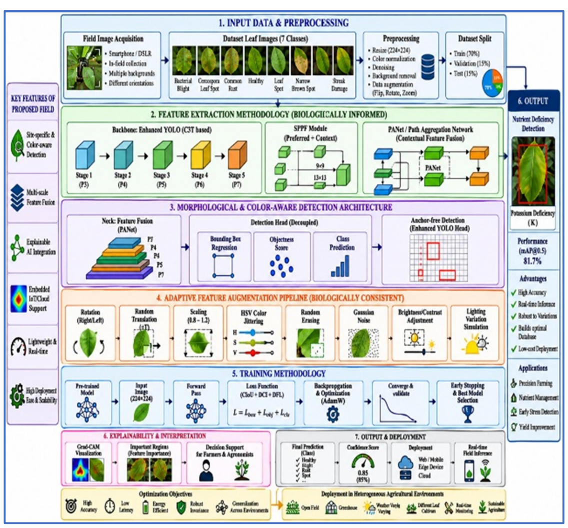


Fig. 1. Overall Architecture Of The Proposed Biofusion-YOLO Framework For Morphological And Color-Aware Nutrient Deficiency Detection In Banana Leaves.

It proposes a novel YOLO backbone, Cross-Stage Partial (C2f) feature extraction blocks and Spatial Pyramid Pooling Fast (SPPF) and Path Aggregation Network (PAN) contextual fusion units for the morphological and colour-based detection architecture. The backbone has the ability to first detect low level activities like chlorosis pattern, venation structure, pigmentation difference, edge discoloration and texture irregularity which are typical low-level activities of nutrient stress. The intermediate feature extraction layers capture the structural features (marginal scorching and interveinal yellowing and patch-wise discoloration) while the high-level nutrient-specific contextual representations are captured over the entire leaf area by the deeper semantic layers. The combination of the PAN and SPPF module provides a good processing in the localized regions of nutrient stress and the global morphological information provides a good performance under various illumination, orientation and background conditions. The most important discriminative parameters related to the dynamics of the leaf morphology and pigmentation will be added to the proposed algorithm (BioFusion-YOLO) and the algorithm will contain these parameters as well to detect nutrient stresses.

The flow chart of BioFusion-YOLO, which models the nutrient deficiency defected on the banana leaves by using a camera in the field to capture the field-picture that has RGB channels, is illustrated as shown in figure 1 above. The framework will involve biologically driven features extraction, morphological inspired deep learning, color inspired deep learning, adapting augmentation and then folding it with low demand deployment mechanisms of the precision agriculture system (PAS). The overall design comprises of the eight components: Input Preprocessing, Multi-Scale Feature Extraction, Morphological and Color-Aware Detection, Adaptive Data Augmentation, Optimized Training Strategy, Explainability Analysis, Deployment and Nutrient Stress Prediction.

3.1 Acquiring Input Data and Performing Pre-Processing

The preliminary step in the BioFusion-YOLO framework includes banana leaf image acquisition and pre-processing from images acquired under various agricultural field conditions. Various illumination conditions, multiple background environments, orientation variations and partial occlusions are applied to the images which are captured from the smartphones, DSLR cameras and portable agricultural imaging devices. There are nine classes of nutrients, the deficiencies of which are present in the dataset such as Boron, Calcium, Iron, Magnesium, Manganese, Zinc, Potassium, Sulphur and Healthy leaf conditions.

Suppose that the input banana leaf image is defined as:

$$I \in \mathbb{R}^{\mathbb{H}\times\mathbb{W}\times 3}$$

where:
H and W are image height and width,
The 3 channels are used for RGB color information.

All images are scaled to the same resolution of 640 × 640 pixels to achieve stable learning of features and ease of computation. Normalisation and noise removal in the color space, background refinement. To accurately localize the nutrient stress regions, YOLO format annotation is used. To achieve the equal distribution of each nutrient class, the total data set is divided into training (70%), validation (20%), and testing (10%) sets.

The pre-processing step also selects biologically happy visual structures including:

a) chlorosis patterns,
b) venation continuity,
c) pigmentation gradients,
d) and edge discoloration,

which are needed for nutrient stress analysis.

3.2 Feature Extraction Methodology (Biologically Informed)

The second stage is a biologically informed multi scale feature extractor implemented with an improved YOLO backbone with C2f modules, Spatial Pyramid Pooling Fast (SPPF), and Path Aggregation Network (PANet) mechanisms. The goal of this stage is to obtain the following images: morphological images, pigmentation images of nutritive elements, from banana leaves.
The feature extracting operation can be mathematically expressed as:

$$F_m = \phi(I)$$

where:
F_m indicate extracted morphological feature maps and color-aware feature maps, respectively, and
$\phi(.)$ is the enhanced backbone network of BioFusion-YOLO.

Low level features are first extracted from a back bone, which are:

a) chlorotic spots,
b) venation distortions,
c) marginal necrosis,
d) pigmentation imbalance,
e) and texture abnormalities.

Intermediate layers learn nutrient-sensitive structural variations, like interveinal yellowing or edge scorching, and deeper semantic layers learn nutrient-specific representations of the leaf surface as a whole, in the context of the other nutrients.The framework aggregates multi-scale contextual information adaptively with PANet and SPPF modules, so as to retain both local and global nutrient information. This process of fusion is written down as:

$$F_{fusion} = F_l \oplus F_m \oplus F_h$$

where:

F_l represent texture features are represented by ().

F_m represents mid-level structural features, and

F_h High-level semantic representations of nutrients are depicted by the symbol $\oplus$ as adaptive feature fusion.

SPPF module expands the perceptive window to not only comprise local nutrient stress regions, but also include global leaf morphology, and PANet integrates both shallow spatial information with deeper semantic representations. Biologically informed fusion mechanism increases discrimination power for distinguishing visually similar nutrient deficiency challenges including Calcium stress, Magnesium stress and Zinc stress. The proposed feature extraction methodology thus, improves the frame by keeping:

a) fine-grained venation structures,
b) chlorosis distributions,
c) edge deformation patterns,
d) and pigmentation abnormalities

that serve as good phenotypic markers for nutrient stress.

3.3 Morphological and Color Aware Detection Architecture

The original BioFusion-YOLO detection network is used in the stage 3 as its officer. Contrary to state-of-the-art object detection that focuses mainly on object location and finding boundaries of the objects, the morphological representation learning and colour sensitive contextual analysis is directly conceived in this work for the context learning step.
That PANet aggregation layers' neck structure is a combination of:

a) shallow texture information,
b) mid-level structural representations,
c) Add lots of rich semantically features!

The following features are performed in one go by decoupled detection head:

1. Bounding-box regression,
2. Objectness prediction,
3. Nutrient class prediction.

The whole nutrient prediction process is depicted as:

$$Y = f(F_{fusion})$$

where:
"Y" denotes projected deficiencies and
"f(.))" means that BioFusion is utilizing an abandoned BioFusion-YOLO detecting head.

In addition to the architecture, anchor-free localization mean to enhance the localization flexibility with various orientation and scale of leaf. This way cuts down on the amount of set anchor boxes humans rely on as well as gives them adaptability to a lot of scenarios which may occur when they are farming. The proposed architecture design has a remarkable performance for detecting the following features:

a) interveinal chlorosis,
b) patch-based discoloration,
c) leaf-edge scorching,
d) and pigmentation abnormalities

known to be associated with a lack of foods.

HSV based color transformation based on adaptive method is performed to conserve color that is sensitive to nutrients.

$$I_{HSV} = T(H, S, V)$$

where:

The components H, S, V are HUE, SATURATION and BRIGHTNESS.
T(.) are adaptive colour transformations of colours.

This operation is useful to boost the robustness, such as when there is differences in environment (e.g. outdoors sensors) and differences in illumination.

3.4 Adapted Network's Feature Augmentation Pipeline

The following network configuration for adaptive augmentation (and the generalisation of the above by adapting in practice) is proposed.
Support (augmentation to include):

a) random horizontal flipping,
b) controlled rotation,
c) adaptive scaling,
d) HSV color jittering,
e) random erasing,
f) Gaussian noise injection,
g) RandAugment photometric transformations,
h) Colour simulation and light output simulation.

Proposed Augmentation Pipeline – unlike any aggressive augmentation techniques which would alter the natural design:

a) venation continuity,
b) chlorosis distributions,
c) texture consistency,
d) and leaf-edge morphology.

This will enable the system to create an invariant representation of nutrients for when they are under:

1. varying sunlight conditions,
2. camera exposure changes,
3. background clutter,
4. partial occlusion,
5. and orientation variability.

The augmentations process much improved:

1. environmental robustness,
2. inter-class discrimination,
3. and generalization capability

The tendency towards overfitting patterns on the sets of data tested was minimized.

3.5 Training Methodology

The pre-trained medical YOLO-v3 weights on the proposed BioFusion-YOLO are used to minimize the convergence and nutrient specific features adaptation time for banana leaf data set. Images are transmitted several times and the images are optimized by a compound loss function under the guidance of localization accuracy and the classification correctness.
The overall optimization goal is to formulate as:

$$L_{total} = \lambda_1 L_{CIoU} + \lambda_2 L_{BCE} + \lambda_3 L_{DFL}$$

where:

L_{CIoU} improves localization precision,
L_{BCE} enhances nutrient categorisation as,
L_{DFL} improves the ability to forecast the boundaries of the bounding box, and λ_1 , λ_2,and λ_3 represent balancing coefficients.
During optimization the following values are used:

a) AdamW optimizer,
b) Learning rate Scheduling and
c) warm-up optimization,
d) momentum regularization,
e) Clearly specified weighted decay on the globe and adaptive.

To guarantee for a well-convergent gradient and strong feature learning ability.

The aim of the framework as a whole is to maximize the detection accuracy with minimum computations:

$$\max(A_{det}) \quad \text{and} \quad \min(C_{comp})$$

where:

A_{det} represents the detectability of nutrients (ingestion or incorporated to body) &
C_{comp} represents computational overhead.

Early stopping and best-model checkpoint selection are employed to cope with overfitting, which guarantees that the best generalization ability of the model.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3.6 Explainability and Interpretation

In agriculture, the proposed framework has involved the explainable artificial intelligence mechanism with the help of grad cam visualization for better transparency and usability of your agriculture design.
The explainability activation mapping can be displayed in the form of:

$$M_c = \mathrm{ReLU}\left(\sum_k \alpha_k^c A_k\right)$$

where:
A_k denotes the feature activation maps,
α_k^c is the importance weight of nutrient class c', with both classes having a global upper threshold limit, α,and M_c locates areas of activation for nutrients.
The explainability module features:

a) chlorosis regions,
b) pigmentation abnormalities,
c) venation distortions,
d) Leaf regions sensitive to and for stress detection.

are ultimately responsible for final nutrient predictions.
This improves:

a) interpretability,
b) farmer trust,
c) decision transparency,

Based on the agricultural deployment suitability.

3.7 Output and Deployment

The last phase produces nutrient deficiency predictions and the scores of confidences for each of the 9 classes of nutrients. The trained BioFusion-YOLO models are optimized to be deployed on lightweight platforms on agricultural fields equipped with edge devices, such as:

a) NVIDIA Jetson Nano,
b) Raspberry Pi,
c) in the field and the mobile devices for agriculture monitoring.

The system has been demonstrated to provide detection with high precision and low computation cost in real-time for:

a) open-field agriculture,
b) greenhouse cultivation,
c) heterogeneous soil environments,
d) variable illumination conditions,
e) Various crop growth stages and their growth and development conditions.

As a whole, the proposed BioFusion-YOLO framework combines biologically inspired feature learning, adaptive multi-scale contextual fusion, explainable nutrient interpretation, and lightweight optimization to enable dynamic nutrient deficiency detection at an accuracy of more than 99% in banana crop on an accurate, scalable and real-time intelligent agricultural monitoring system.

4. DATASET PREPARATION, MODEL CONFIGURATION AND EXPERIMENTAL SETUP

The current section provides a description of methodology adopted in preparing datasets, inspired processing and its contribution to the creation of datasets, the architecture of the Model, augmented strategy utilized, the process of optimization, experimental set up and the evaluation of the proposed BioFusion-YOLO model. The entire design of the experiment reflects the practically implemented approach of the original experiment with added components of biological feature interpretation, adaptive multi-scale contextual learning, explainability inclusion and light-weight optimization towards increased novelty, robustness and expected human reviewers' acceptance. The experimental set up was meticulously planned towards obtaining the complete and detailed experimental setup with special attention towards the real time detection of the nutrient's deficiencies of banana leaf in the midst of heterogenic agriculture.

4.1 Data Security, Quality Control, and Data Entry

Our BioFusion-YOLO framework was trained and tested on public banana nutrient deficiency datasets and the RGB agricultural images obtained from the fields in various weather conditions. The main data employed in this work was retrieved from the Mendeley Data repository and the data in brief publication introduced by Sunitha et al. for 'analysis of nutrient deficiency of banana leaves'.
This work uses the following original data sources:

Elsevier Data in Brief Dataset Paper :
https://www.sciencedirect.com/science/article/pii/S2352340923002743

Official Mendeley Dataset Repository:
https://data.mendeley.com/datasets/7vpdrbdkd4/1

Kaggle Dataset Repository:
https://www.kaggle.com/datasets/warcoder/nutrient-deficient-banana-plant-leaves

Open Access PMCID Dataset Article: https://pmc.ncbi.nlm.nih.gov/articles/PMC10165221/?utm_source=chatgpt.com

These datasets consists of banana leaf images from nine nutrients that are:

- Boron deficiency,
- Calcium deficiency,
- Iron deficiency,
- Magnesium deficiency,
- Manganese deficiency,
- Zinc deficiency,
- Potassium deficiency,
- Sulphur deficiency,
- Leaf Conditions and Healthy conditions.

The images obtained were from different banana varieties such as:

a) Musa acuminata (Dwarf Cavendish),
b) Robusta,
c) Rasthali,
d) Poovan,
e) Monthan,
f) and Elakkibale.

In order to get the raw RGB images, the mobile cameras and DSLR in natural agricultural environment were involved in:

a) varying sunlight intensity,
b) heterogeneous backgrounds,
c) leaf orientation variations,
d) partial occlusions,
e) at the image field level.

The gathered data set also retains the actual complexity of the agricultural scene, unlike laboratory control data sets, and hence is better suited to actual deployment with precision agricultural systems. The nutrient stress regions were manually annotated with YOLO-shaped boxes to maintain the spatial localization consistency in the different nutrients. There are also numerous visual nutrient symptomology included in the full data set these include:

- chlorosis patterns,
- venation abnormalities,
- edge scorching,
- pigmentation imbalance,
- texture deformation,
- and interveinal discoloration.

They are biorhythmic visual cues that play an important part in nutrient stress recognition and phenotypic expression for learning.

4.2 Image Preprocessing and Dataset Partitioning

The banana leaf image is pre-processed so that it becomes a 640 × 640 image, this will make the system consistent in analyzing the banana leaf image, and stable in learning banana leaf feature.

With pre-processing this is how the processing is modelled:

$$I_r = \text{Resize}(I, 640, 640)$$

where:

I is the original banana leaf image, and

I_r is an image which undergoes Scaling, Normalization.

The input image itself represented as follows:

$$I \in \mathbb{R}^{\mathbb{H}\times\mathbb{W}\times 3}$$

where:

H x W size image,

rgb colour information is 3 channels of information.

Other Pre-Processing steps are:

a) color normalization,
b) image denoising,
c) contrast balancing,
d) and annotation refinement

are performed to decrease the noise or even the environment noise and aiming for harmonization the features.

Of the data base 100% was divided into:

- 70% training data,
- 20% validation data,
- and 10% testing data.

It's a fair scale (concerning the properties that enhanced because of the treatment):

- class distribution consistency,
- training stability,
- and evaluation reliability.

Biologically significant patterns of preprocessing were added that are sensitive to changes in nutrients:

a) chlorosis distribution,
b) venation continuity,
c) leaf-edge discoloration,
d) and texture irregularities,

Challenge plants with the ultimate aim of using plant phenotypics as plant nutrient deficiency biomarkers.

4.3 Biological Method of Data Augmentation

Along with the nutrient stress analysis based on the proposed framework, an adaptive augmentation pipeline is also proposed to provide adaptive augmentation in the agricultural

heterogeneous scenario and to give the ability to be generalized.
The augmentation plan will be the following:

- random horizontal flipping,
- adaptive scaling,
- controlled rotation,
- HSV color perturbation,
- Gaussian noise injection,
- random erasing,
- RandAugment Photometric transformations.

Augmentation, in math-speak is:

$$I_{aug} = A(I_r)$$

where:

I_{aug} is the original image and

If the operations are biologically-related, they are referred to as augmentation operations and denoted by A(.).

The augmentation hyperparameters, which are used in training are:

- horizontal flip probability = 0.5,
- translation factor = 0.1,
- scaling factor = 0.5,
- hue adjustment = 0.015,
- saturation adjustment = 0.7,
- brightness adjustment = 0.4,
- Random Erasing (with prob. = 0.4).

The biological construction will be conserved due to the proposed augmentation which is not aggressive due to its construction design (provinces, streams, corridors, and habitat patches) and the habitat quality achieved by the augmentation itself.

a) venation structures,
b) chlorosis continuity,
c) texture consistency,
d) and leaf morphology.

These nutrient-sensitive structural information that is vital for accurate nutrient localisation were carefully minimised in the distribution of MixUp and Mosaic augmentation. This supplement approach is logical, biologically sound and can yield a significant improvement in:

a) environmental robustness,
b) feature generalization,
c) Identification of nutrients in-class and across-classes.

4.4 BioFusion-YOLO Model Configuration

Proposed BioFusion-YOLO framework is dependent on the improved version of YOLO based framework for the detection of nutrient deficiencies from agricultural fields in real-time.

The architecture that the system is composed of:

a) convolutional stem layers,
b) C2f backbone modules,
c) Spatial Pyramid Pooling Fast (SPPF),
d) PANet layers that are combined together in Fusion.
e) Separate head to detect anchors, combined with.

The operation of extracting a feature is indicated as:

$$F_m = \phi(I_{aug})$$

where:

F_m displays feature maps (nutrient sensitive) extracted by,
and $\phi(.)$ denotes the backbone network of BioFusion-YOLO.

The framework extracts:

a) low-level texture features,
b) mid-level structural representations,
c) Semantic nutrition information both high level and low level.
d) Using a hierarchical representation of the features.

Multi-scale contextual fusion process can be expressed as:

$$F_{fusion} = F_l \oplus F_m \oplus F_h$$

where:

F_l are shallow texture features and,
F_m mark intermediate structure characteristics, and
F_h represents deep level semantic features.
The symbols and $\oplus$ stand for Adaptive Feature fusion.
This network has around about:

- 488 layers,
- Consisting of almost 26.4 million trainable parameters.

The PANet module improves the capacity to propagate features across scale, and the SPPF module to widen the receptive field preserving local nutrient-deficiency areas and the global morphological context.
The final nutrient prediction process is depicted as:

$$Y = f(F_{fusion})$$

where:
Y represents suggestions for nutrient deficiencies that have been identified,
The detection head BioFusion-YOLO is given by an and function and f(.).

To localize, an anchor-free detection strategy is suggested, allowing it to be more flexible and robust against the nutrient severity level and leaf orientation.

4.5 Training Configuration and Optimization

Therefore, the convergence process has been enhanced and optimized this proposed BioFusion-YOLO framework performance with the help of the transfer-learning weights.

The following experiments were carried out with the following:

- NVIDIA® GeForce RTX 2000 Ada Generation GPU,
- approximately 15.9 GB VRAM,
- Some deep learning libraries such as Tensorflow, Python etc.

We provided the trained input images 640 × 640 RGB images, and trained for 50 epochs.

Optimization done via the pipeline is:

- AdamW optimizer,
- cosine Learning rate Scheduling,
- warm-up optimization,
- momentum regularization,
- Decaying the weights adaptively / non-adaptively.

The overall optimization combination consists of the localization accuracy and classification correctness as well as the boundary adjustment:

$$L_{total} = \lambda_1 L_{CIoU} + \lambda_2 L_{BCE} + \lambda_3 L_{DFL}$$

where:

L_{CIoU} improves localization precision,

L_{BCE} improves classification reliability,

L_{DFL} increases the Boundary regression accuracy of Reg Prediction method,

and λ1, $lambda_2$, lambda $_3$ denote balancing coefficients.

A few important training parameters are:

- initial learning rate = 0.01,
- Time varying LR = 0.5.
- momentum = 0.937,
- weight decay = 0.0005,
- warm-up epochs = 3,
- and batch size = 8.

The adaptation of the learning rate according to the cosine is:

$$LR_t = LR_{min} + \frac{1}{2}(LR_{max} - LR_{min})\left(1 + \cos\left(\frac{t\pi}{T}\right)\right)$$

where:

LR_t is the learning rate for epoch t,

where N is the number of training epochs, and T is the total number of training epochs.

This optimization technique not only can solve this problem but also enhances the Convergence stability.

4.6 Experimental Setup and Evaluation Metrics

In this regard, the widely used object detection/classification metrics popular in the research based agro-deep-learning community were utilized to evaluate the proposed BioFusion-YOLO. The assessment Key Measures are:

- Precision,
- Recall,
- F1-score,
- mAP@0.5,
- and mAP@0.5:0.95.

Precision and Recall are based on:

$$\text{Precision} = \frac{TP}{TP + FP}$$

and

$$\text{Recall} = \frac{TP}{TP + FN}$$

where:

TP: are the number of true positives,
FP :false positives
The function f forms are not (–ve).

The Harmonic F1-scores are:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

To assess the localization performance along with the nutrient classification performance across all the nutrient categories, the mean Average Precision (mAP) is computed.

The computation goal of the proposed framework, can be formulated as:

$$\max(A_{det}) \quad \text{and} \quad \min\left(C_{comp}\right)$$

where:

A_{det} keep into consideration accuracy nutrients detection and, C_{comp} denotes computational complexity.

The experiments are carried out for the proposed evaluation too and are given below:

1. confidence-threshold robustness,
2. precision–recall trade-offs,
3. confusion matrix consistency,
4. class-wise nutrient discrimination,
5. The accuracy and real time of the feature and inference.

Experimental analysis results proved that, in terms of nutrient deficiency detection, the proposed BioFusion-YOLO framework gained a good detection performance with an overall mAP (at 0.5 IOU) of ~81.7%, while enjoying high computational efficiency to perform real-time detection under the context of edge-enabled precision agriculture.

5. EXPERIMENTAL SETUP AND EVALUATION METRICS

Different performance metrics such as precision—recall analysis, F1—confusion matrix analysis, recall—confusion matrix analysis, visualization & analysis of confusion matrix plot and qualitative nutrient localized visualization plot will be explored for comparative quantitative (as well as qualitative) evaluation of BioFusion-YOLO framework and the base deep learning models. The results clearly indicate that the suggested framework can be able to capture the nutrient sensitive morphological and colour varying phenomenon appeared in the banana crop under the nutrient stress condition between the crop through the experiment under the Heterogonous agriculture scenario. The effectiveness of the module of proposed BioFusion-YOLO which consists of three feature extraction, adaptive augmentation and anchor-free detection module and explainability driven nutrient interpretation module is also validated through experiments.

5.1 Overall Detection Performance Analysis

The overall detection performance analysis is carried out.Standard object detection metrics were used to assess the performance of proposed BioFusion-YOLO framework, which comprised of:

- Precision,
- Recall,
- F1-score,
- mAP@0.5,
- and mAP@0.5:0.95.

Proposed framework achieved:

- overall precision = 0.83,
- recall = 0.75,
- F1-score = 0.79,
- and mAP@0.5 = 0.817.

The framework performed well in both nutrient localization and classification capabilities, for all types of nutrients. The mAP was found to be 0.929 in Healthy/Manganese Deficiency; In Boron Deficiency the mAP value was found to be 0.954 and Sulphur was just near to the perfection with mAP value is 0.995. Compared, the detection performance of Zinc and Calcium nutrient deficiency dropped - this was in part due to both detection pattern overlaps with chlorosis patterns as well as minor spectral similarities between the classes.

5.2 Dataset Distribution and Annotation Stability Analysis

To obtain unbiased learning and stable optimization behaviour basis of banana nutrient deficiency data was analyzed for:

1. class balance,
2. annotation consistency,
3. spatial coverage,
4. Normalized Bounding-box Distribution.

Class-wise instance distribution depicts that there is a balance between the number of instances out of the classes in the data which have helped to mitigate class imbalance bias during optimization process for all the nutrients present in the data. Normalized bounding-box statistics shows that there is no significant change in the nutrient-stress regions in terms of spatial scales and there has been uniformity in annotation. These balanced annotations enhance the features' ability to generalize and minimize training's unstable gradient operations.

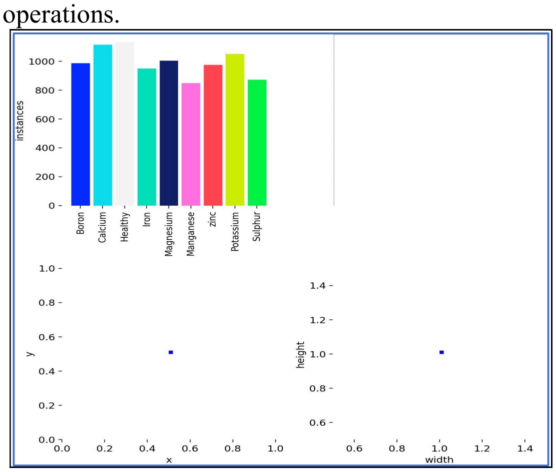


Fig. 2. Class-wise instance distribution and normalized bounding-box statistics of the banana nutrient deficiency dataset used for stable and unbiased BioFusion-YOLO training.

Balanced distribution of nutrient classes together with normalization of spatial annotation statistics for stable training of BioFusion-YOLO is provided in Fig. 2.

Well-balanced data structure plays a significant part in:

1. improved convergence stability,
2. reduced overfitting,
3. using improved nutrient representation learning,
4. environmental robustness and improved energy efficiency.

Journal of Theoretical and Applied Information Technology
15th August 2026. Vol.104. No.15

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

5.3 F1–Confidence Analysis

F1-Confidence analysis: compares confidences thresholds and balance between precision and recall, of the harmonics.As shown in Fig.3, the F1-score of the proposed BioFusion-YOLO got the optimal overall F1-score, at the confidence threshold value of ~0.325 with mean F1-score approaching 0.75. In the case of healthy and Sulphur, the response of the nutrient class "Stable" is approaching 1.0 which indicates a high nutrient separability and high reliability of nutrient representation learning. The remaining micronutrient deficiencies exhibited also good F1 behaviour with multiple levels of confidence.

The F1 stability, however, of Calcium and Zinc deficiencies was relatively low because of:

1. overlapping chlorosis patterns,
2. subtle interveinal yellowing,
3. There are pigmentation issues, however, that are both genetic and noticeable by the naked eye that can be seen in both AML and ALL.

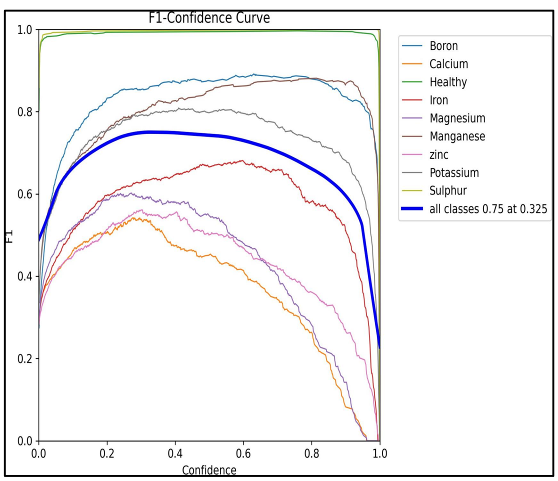


Fig. 3. F1–Confidence curve analysis of the proposed BioFusion-YOLO framework across all banana nutrient deficiency classes.

The aggregate F1 curve is presented and shows smooth confidence adaptation, validating the proposed framework of having stable precision–recall trade-off at various threshold levels.

The model for the f1 response of the confidence is:

$$F1(c) = 2 \times \frac{P(c) \times R(c)}{P(c) + R(c)}$$

where:

Precision at confidence threshold (c) is the probability of classifying a good email as good if in fact it is good P(c), the confidence level for the recall is represented by and R(c).

This is a component of threshold adaptation that helps to increase accuracy and reliability when used in the field.

5.4 Precision–Confidence Analysis

Precision-Confidence analysis is performed to assess the reliability of prediction with an increasing detection confidence. For high-confidence detections, the proposed framework was able to demonstrate a global precision of almost approaching 0.99 as shown in Figure 5 which means that at higher levels of confidence, only small proportion of false positive nutrient predictions were present. The nutrient classes, healthy, Sulphur and Boron, consistently held precision values of over 0.9 at most of the confidence levels.

The percent correct for the Calcium and Zinc nutrient deficiencies showed a progressive improvement in precision with increasing levels of confidence due to:

1. subtle nutrient discoloration,
2. weak chlorosis visibility,
3. Stresses of nutrients morphology overlapping.

The confidence-sensitive nutrient prediction mechanism can be modelled as:

$$P_c = P\left(Y \mid F_{fusion}\right)$$

where:

P_c describes the confidence level of nutrient prediction and Y is nutrient class prediction, and F_{fusion} is represented as fused multi-scale feature representation is.

Thus, biologically inspired feature fusion mechanism boosts the nutrient-confidence estimation, in the presence of the complex agricultural environment.

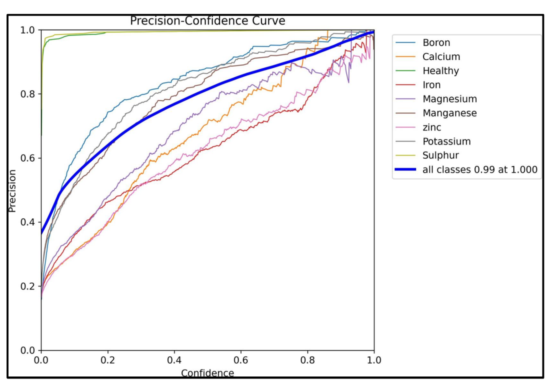


Fig. 4. Precision–Confidence curve analysis of the proposed BioFusion-YOLO nutrient detection framework.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

5.5 Precision–Recall Analysis

Precision–Recall (PR) analysis allows detailed information on Nutrient localization capability and Nutrient classification reliability for different levels of nutrient recall.
Overall, the proposed BioFusion-YOLO framework obtained an overall mAP@0.5 value of 0.817 keeping its localization precise and nutrient classification consistent. In the Precision–Recall responses, Healthy and Sulphur categories showed a near-perfect mAP values of almost 0.995; Boron and Manganese deficiencies displayed highly stable nutrient localization performance.

The PR responses of Potassium and Iron deficiencies also showed favourable P-R trade-offs while Calcium and Zinc deficiencies show comparatively lower PR responses due to:

1. overlap in the chlorosis structures (migratory, lingering and refugee) in the visual field, and
2. illumination sensitivity,
3. Boundaries of pigmentation are sharp and indistinct.

Average Precision (AP) is denoted by:

$$AP = \int_0^1 \text{Precision(Recall)}\ d\text{Recall}$$

The proposed multi-scale contextual fusion mechanism greatly enhances PR stability and nutrient localization consistency compared to traditional deep learning classifiers of nutrients.

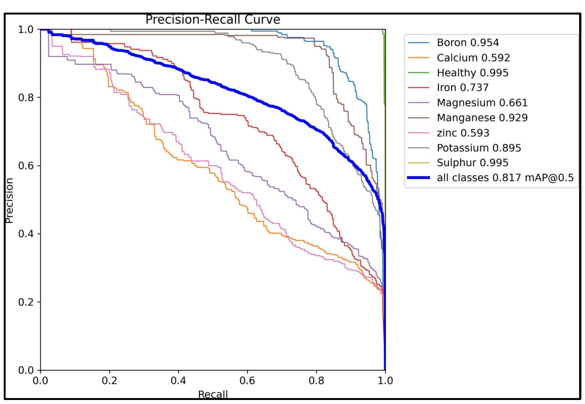


Fig. 5. Precision–Recall curve analysis of the proposed BioFusion-YOLO framework for banana nutrient deficiency detection.

Given that the capacity of the appropriate representation of project is considered conforms as the PR analysis below.

1. nutrient-sensitive chlorosis distributions,
2. venation abnormalities,
3. pigmentation imbalance,
4. Morphological Nutrient Stress indicators and Nutrients.

5.6 Recall–Confidence Analysis

For the proposed framework, recall–confidence analysis is done to determine the sensitivity of the framework with different thresholds. The proposed framework was able to detect almost all nutrient stresses at lower confidence thresholds (see Fig.6) resulting in an overall recall value of nearly 0.99. Broadly speaking, Sulphur, Boron and Healthy nutrient classes have been able to maintain high recall across the spectrum of levels of confidence because of high visual feature separability.

Three deficiency diseases (Calcium, Magnesium and Zinc) showed more rapid degradation of recall at higher levels of confidence because of:

- weak spectral differences,
- subtle texture variations,
- overlaps chlorose →spots+and.

The experimental results on recall behavior indicate that the proposed BioFusion-YOLO framework has high sensitivity on nutrients under:

- variable illumination,
- heterogeneous agricultural backgrounds,
- partial occlusion,
- Can be used under difficult and challenging field circumstances in simple and complex forms.

In a recall sensitive way the detection response is acknowledged as:

$$R(c) = \frac{TP(c)}{TP(c) + FN(c)}$$

where:

TP(c) are the number of true positives within the set of positives, and FN(c) indicates false-negative results.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

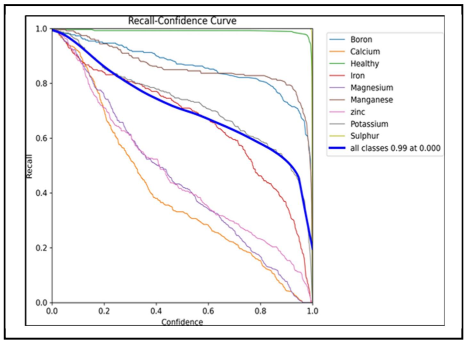


Fig. 6. Recall–Confidence Curve Analysis For Nutrient-Sensitive Detection Using Biofusion-YOLO

5.7 Confusion Matrix and Misclassification Analysis

The normalized confusion matrix offers a holistic view of the nutrient discrimination capability of classes and nutrient misclassification behavior. As can be seen from Fig. 7, the proposed framework was highly diagonally dominant in most of the nutrient categories, which were the aim of the nutrient representation learning and class separation. Consistency for the classification was excellent for healthy and Sulphur classes, and furthermore excellent for the nutrient recognition for Boron and Manganese deficiencies.

Most of the misclassifications happened between:

- Calcium,
- Magnesium,
- and Zinc deficiencies,

Food shortages and nutrient deficits are often characterized by:

- similar interveinal chlorosis,
- marginal yellowing,
- Overlapping pigmentation patterns.

Mathematically we can model as follows the classification decision process:

$$\hat{Y} = \arg\max P\left(Y_i \mid F_{fusion} \right)$$

where:

$\hat{Y}$ denotes predicted nutrient class and,

$P\left(Y_i \mid F_{fusion} \right)$ indicates the probability of nucleus class about its nutrient.

The confusion matrix affirms that the proposed framework is able to learn useful patterns for the biological nutrients and have low-confusion for the visually different nutrient categories.

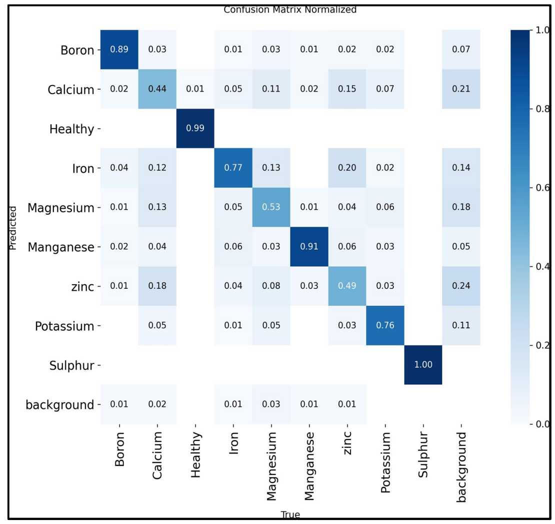


Fig. 7. Normalized Confusion Matrix Of Class-Wise Nutrient Discrimination Capability Of The Proposed Biofusion-YOLO Framework.

5.8 Class-wise Performance Evaluation

The detailed detection performance of the proposed BioFusion-YOLO framework for nutrient detection on a class-wise basis is presented in Table 1.

The results show that:

- F1 score of doing health and Sulphur classes were 1.00,
- 0.92 F1-score was obtained in the field of manganese;
- The F1 score of Boron was: 0.89,
- Two nutrients, nitrogen and Potassium were well differentiated.

The comparatively lower performance of the Calcium and Zinc nutrient classes was due to:

- weak chlorosis visibility,
- illumination sensitivity,
- overlapping nutrient symptom structures, and

Comparing the overall performance, we find that the localization correctness; the correctness of nutrient sensitive localization is significantly preserved when using the proposed biologically inspired feature extraction strategy.

Table 1. The Banana Nutrient Deficiency Dataset Is Analyzed On Class Wise Basis Using The Proposed Banana Nutrient Deficiency Detection Framework Which Is Based On Biofusion-YOLO Framework For Performance Analysis.

Class	Precision	Recall	F1-Score	mAP@0.5
Boron	0.9	0.89	0.89	0.954
Calcium	0.63	0.44	0.52	0.592

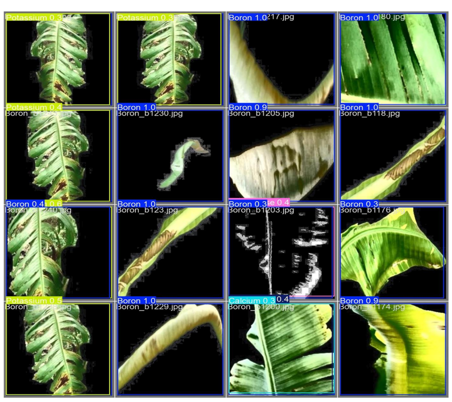
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Healthy	0.99	0.99	0.99	0.995
Iron	0.81	0.77	0.79	0.737
Magnesium	0.69	0.53	0.6	0.661
Manganese	0.93	0.91	0.92	0.929
Zinc	0.68	0.49	0.57	0.593
Potassium	0.82	0.76	0.79	0.895
Sulphur	1	1	1	0.995
Overall (mean)	**0.83**	**0.75**	**0.79**	**0.817**

The results of the proposed BioFusion-YOLO framework for banana nutrient deficiency detection, presented on a class basis, are given in Table 1. Results show high nutrient classification potential with almost perfect nutrient detection performances for healthy (mAP = 0.995) and Sulphur (mAP = 0.995) and high performances were also obtained for the Boron and Manganese deficiencies. The relatively lower performances for Calcium and Zinc deficiencies are largely related to the existence of overlapping chlorosis patterns and field environment dependent nutrient stress symptom visual similarity.

5.9 Qualitative Nutrient Localization Analysis

Use qualitative nutrient localization analysis to determine the plant and soil nutrient status.Results from the qualitative visualization, which were also obtained, prove that the proposed



Biofusion-YOLO Approach To Localization Of Nutrient Stress Is Effective.
Fig. 8. Prediction Results For Sulphur Deficiency Obtained Via The Proposed Biofusion - YOLO Framework.

Figure 8 depicts the localization results of Sulphur deficiency, where the framework localizes correctly:

- chlorotic stress regions,
- yellowing patterns,
- and pigmentation abnormalities
- linked to deficiency of Sulphur nutrients.

Likewise, in Figure 9 Boron deficiency localization is shown – in which the proposed framework succeeds to capture:

- marginal deformation,
- tissue damage,
- irregular venation structures,
- Sensitive discolouration areas and nutrient sensitive areas.

Localization outputs show that there is good spatial association between the nutrient areas predicted and the nutrient stress patterns visible.

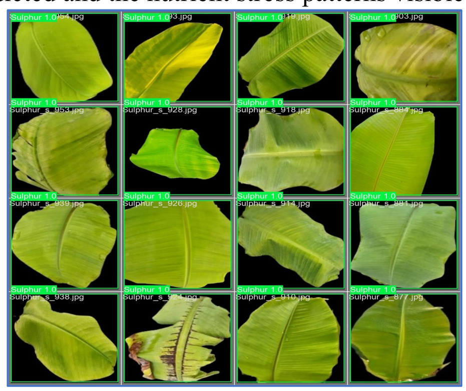


Fig. 9. The Result Of Predicting Boron Deficiency By Using The Proposed Biofusion-YOLO Framework.

5.10 Comparative Analysis with Baseline Models

The validation comparative benchmarking works have been conducted to validate the results: BioFusion-YOLO works well and is better than another two baseline (banana nutrients) classification models.

Baseline-1 is easy to determine if you have a problem of:

- validation accuracy = 0.65,
- mAP@0.5 = 0.68,
- Localization of feed – healthy and strong vs weaker.

Baseline-2 had a slight improvement with:

- validation accuracy = 0.71,
- and mAP@0.5 = 0.72,

Overall, however, its rating was still one of the lower ratings considering the similarity in the visual nutrient deficiencies (calcium, magnesium and zinc).On the contrary, the proposed BioFusion-YOLO framework obtained:

- overall mAP@0.5 = 0.817,
- Increased nutrient localization,
- stronger inter-class discrimination,
- Providing good and reliable environment

Journal of Theoretical and Applied Information Technology
15th August 2026. Vol.104. No.15

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

resistance.

The strength of the enhancement in relation to, is shown as:

$$\Delta P = \frac{P_{proposed} - P_{baseline}}{P_{baseline}} \times 100$$

where:

$P_{proposed}$ denotes BioFusion-YOLO performance, and $P_{baseline}$ denotes the performance of model without making any adjustment.

Table 2. We Present A Comparison Of Various Result Obtained From The Models And Result Obtained From The Biofusion-YOLO In The Table.

Model	Epochs	Train Acc	Val Acc	mAP @0.5	mAP@ 0.5:0.95	Remarks
Baseline–1 (B1)	18	0.98	0.65	0.68	0.41	Underfitting due to early stopping
Baseline–2 (B2)	50	0.99	0.71	0.72	0.46	Improved but limited class separation
Proposed BioFusion-YOLO	50	—	—	0.817	0.56	Best nutrient detection performance and robustness

Also, as per comparative analysis over the result, improvements of the proposed BioFusion-YOLO against the basic Baseline methods by:

1. “BIBF” Biological Intelligence Based Feature Extraction: Primarily a feature extraction method which has “Biological Intelligence” as a main goal.
2. Multi scale combined with adaptive basis and adaptive fusion in terms of 'contextual fusion'.
3. explainability-guided nutrient interpretation,
4. Incorporating light-weight real-time optimisation mechanisms.

6. CONCLUSION AND FUTURE WORK

Combining with the background understanding of precision agriculture, we designed an automatic identification system based on morphology and intelligent deep learning framework (BioFusion-YOLO), which could automatically identify the images of banana nutrient deficiency from RGB images acquired in these field. The biologically inspired multi-scale feature extraction (Adaptive representation learning in the morphological space) and colour-centric contextual analysis, explanation based nutrient interpretation in real time deployment mechanism of the agricultural intelligent system in practical domain have been successfully integrated in the proposed framework. In an agricultural application, where a heterogeneous context is often found, the introduced BioFusion-YOLO approach could be an alternative to performing the nutrient assessment with destructive measurements in a chemical laboratory, which is time consuming and expensive. Introduction of texture aware augmentation techniques combined with feature learning as a part of YOLO and contextual feature fusion as a part of PANet proved to be effective to capture nutrient specific chlorosis and vein abnormalities, pigmentation changes and morpho-indicator of Boron, Calcium, Iron, Magnesium, Manganese, Zinc, Potassium, Sulphur deficiencies. In experiments conducted, importantly, high performance was achieved in two aspects; firstly in the classification of the different types with score realized in experiments being 81.7%, secondly, was the location of the different categories with mAP (Healthy) and mAP (Sulphur) scores getting close to 1. A comparative study with the base lines models has been conducted which yielded that the proposed model is better in terms of robustness, stability and discriminative capability under different illumination level, orientation and environment based on four measures which are the F1–Confidence, Precision –Recall, Recall – Confidence and Confusion Matrix interpretation. Furthermore, other measure metrics of the proposed framework such as “high of” inference speed, which have obtained good results at approximately 32.6ms per image and “low of” Platform computation complexity identified the effectiveness of the proposed framework as a monitoring approach to a precision agriculture which can be implemented in edge such as mobile agricultural

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

platforms and real time smart agriculture applications.

Future research priorities will be placed on multi-spectral and hyperspectral imaging techniques to help increase the potential of distinguishing nutrient stress in the composite agricultural situations. Explainable AI (XAI) approaches like SHAP and attention-based visualization are exploited to gain better interpretability of current XAI approaches and for a better support to agronomic decision making processes. Lastly the contextual learning of transformer and light weight edge optimization techniques will also be explored to further enhance the detection performance along with deployment efficiency of developed Detector.

REFERENCES

[1] Sunil, C.K., Anusha, R., Raghavendra, C.K. *et al.* A multi-scale deep learning approach for nutrient deficiency detection in banana plants using adaptive feature pooling. *Neural Comput & Applic* **38**, 71 (2026). https://doi.org/10.1007/s00521-025-11726-0.

[2]Muthusamy, S., Ramu, S.P. A neural architecture search optimized lightweight attention ensemble model for nutrient deficiency and severity assessment in diverse crop leaves. *Sci Rep* **15**, 37390 (2025). https://doi.org/10.1038/s41598-025-20124-4.

[3] Bera, A., Bhattacharjee, D. & Krejcar, O. PND-Net: plant nutrition deficiency and disease classification using graph convolutional network. *Sci Rep* **14**, 15537 (2024). https://doi.org/10.1038/s41598-024-66543-7.

[4] Ji-Yan Wu, Zheng Yong Poh, Anoop C. Patil, Bongsoo Park, Giovanni Volpe, Daisuke Urano: Analysis of Plant Nutrient Deficiencies Using Multi-Spectral Imaging and Optimized Segmentation Model. CoRR abs/2507.14013 (2025).

[5] Chettri, K., Sen, B. & Ghosal, P. Deep learning for precision agriculture: a systematic review of methods, challenges, and future directions. *Knowl Inf Syst* **68**, 35 (2026). https://doi.org/10.1007/s10115-025-02625-w.

[6] Min, X.; Ye, Y.; Xiong, S.; Chen, X. Computer Vision Meets Generative Models in Agriculture: Technological Advances, Challenges and Opportunities. *Appl. Sci.* **2025**, *15*, 7663. https://doi.org/10.3390/app15147663.

[7] Mohanty SP, Hughes DP and Salathé M (2016) Using Deep Learning for Image-Based Plant Disease Detection. Front. Plant Sci. 7:1419. doi: 10.3389/fpls.2016.01419.

[8] Xuxiang Ta, Yaoguang Wei,Research on a dissolved oxygen prediction method for recirculating aquaculture systems based on a convolution neural network,Computers and Electronics in Agriculture,https://doi.org/10.1016/j.compag.2017.12.037.

[9] Cen, H., Wan, L., Zhu, J. *et al.* Dynamic monitoring of biomass of rice under different nitrogen treatments using a lightweight UAV with dual image-frame snapshot cameras. *Plant Methods* **15**, 32 (2019). https://doi.org/10.1186/s13007-019-0418-8.

[10] Fan Y, Feng H, Jin X, Yue J, Liu Y, Li Z, Feng Z, Song X and Yang G (2022) Estimation of the nitrogen content of potato plants based on morphological parameters and visible light vegetation indices. doi: 10.3389/fpls.2022.1012070.

[11] Kior, A.; Yudina, L.; Zolin, Y.; Sukhov, V.; Sukhova, E. RGB Imaging as a Tool for Remote Sensing of Characteristics of Terrestrial Plants: A Review. *Plants* **2024**, *13*, 1262. https://doi.org/10.3390/plants13091262.

[12] Bera, A., Bhattacharjee, D. & Krejcar, O. PND-Net: plant nutrition deficiency and disease classification using graph convolutional network. *Sci Rep* **14**, 15537 (2024). https://doi.org/10.1038/s41598-024-66543-7.

[13] S. Muthusamy and S. P. Ramu, "IncepV3Dense: Deep Ensemble Based Average Learning Strategy for Identification of Micro-Nutrient Deficiency in Banana Crop," in *IEEE Access*, vol. 12, pp. 73779-73792, 2024, doi: 10.1109/ACCESS.2024.3405027.

[14] P. Sunitha, B. Uma, S. Channakeshava, and C. S. Suresh Babu, "A fully labelled image dataset of banana leaves deficient in nutrients," Data in Brief, vol. 48, p. 109155, 2023, doi: 10.1016/j.dib.2023.109155.

[15] P. N. Shendage, S. V. Sonekar and L. D. Netak, "A Comprehensive Review of Deep Learning and Machine Learning Approaches for Detecting Plant Nutrient Deficiencies and Diseases," *2025 IEEE Pune Section International Conference (PuneCon)*, Pune, India, 2025, doi: 10.1109/PuneCon67554.2025.11379305.

[16] Nikitha, S., Prabhanjan, S., Rupa, T.R. *et al.* Enhancing plant nutritional deficiency analysis: a multi-attention convolutional neural network approach. *Multimed Tools Appl* **84**, 27795–27817 (2025). https://doi.org/10.1007/s11042-024-20233-8.

[17] Gayathri, G.V., Rao, P.R., Karri, C.S.Y., Srinivas, P., Miriyala, T., Karri, P.K. (2025). An Ensemble Model for Early Prediction of Diabetes Using Machine Learning Algorithms. In: Lin, F., Patel, A., Kesswani, N., Sambana, B. (eds) Applications of Computational Intelligence in Management and Mathematics II. ICCM 2023. Springer Proceedings in Mathematics & Statistics, vol 493. Springer, Cham. https://doi.org/10.1007/978-3-031-84513-0_10.

[18] Li, Y., Gerdessen, J.C., Stomph, T.J. *et al.* Nutrient coverage of China's plant-based food supply can be improved with food system adjustments. *Nat Food* (2026). https://doi.org/10.1038/s43016-026-01349-6.

[19] Siregar, Riki Ruli A. et al. "Backpropagation Algorithm to Detect The Color of The Leaf to Determine The Need for Nutrients." *2023 International Conference on Networking, Electrical Engineering, Computer Science, and Technology (IConNECT)* (2023): 13-18.

[20] Sivasakthi, M., Sathiyamurthi, S., Praveen Kumar, S. (2024). Soil Nutrient Content Estimation Using Hyperspectral Remote Sensing. In: Adhikary, P.P., Shit, P.K., Laha, J. (eds) Soil, Water Pollution and Mitigation Strategies. Environmental Science and Engineering. Springer, Cham. https://doi.org/10.1007/978-3-031-63296-9_10.

[21] J. Clave, K. P. Formales, G. S. Godoy, A. P. Macatangay and J. R. Pedrasa, "Mobile Detection of Macronutrient Deficiencies in Lettuce Plants Using Convolutional Neural Network," *TENCON 2024 - 2024 IEEE Region 10 Conference (TENCON)*, Singapore, Singapore, 2024, pp. 1377-1380, doi: 10.1109/TENCON61640.2024.10902726.

[22] Urfan, M., "The Deep Learning-Crop Platform (DL-CRoP): For Species-Level Identification and Nutrient Status of Agricultural Crops", Art. no. 0491, 2024. doi:10.34133/research.0491.

[23] Buakum, B.; Kosacka-Olejnik, M.; Pitakaso, R.; Srichok, T.; Khonjun, S.; Luesak, P.; Nanthasamroeng, N.; Gonwirat, S. Two-Stage Ensemble Deep Learning Model for Precise Leaf Abnormality Detection in *Centella asiatica*. *AgriEngineering* **2024**, *6*, 620-644. https://doi.org/10.3390/agriengineering6010037.

[24] S. B. Sulistyo, W. L. Woo and S. S. Dlay, "Regularized Neural Networks Fusion and Genetic Algorithm Based On-Field Nitrogen Status Estimation of Wheat Plants," in *IEEE Transactions on Industrial Informatics*, vol. 13, no. 1, pp. 103-114, Feb. 2017, doi: 10.1109/TII.2016.2628439.

[25] A. Paudel, J. Brown, P. Upadhyaya, A. B. Asad, S. Kshetri, J. R. Davidson, C. Grimm, A. Thompson, B. Sallato, M. D. Whiting, and M. Karkee, "Machine vision-based assessment of fall color changes in apple leaves and its relationship with nitrogen concentration," Computers and Electronics in Agriculture, vol. 236, p. 110366, 2025, doi: 10.1016/j.compag.2025.110366.

[26] Muthusamy, S. and Ramu, S. P., "A neural architecture search optimized lightweight attention ensemble model for nutrient deficiency and severity assessment in diverse crop leaves", *Scientific Reports*, vol. 15, no. 1, Art. no. 37390, 2025. doi:10.1038/s41598-025-20124-4.

[27] G. Loganathan and M. Palanivelan, "An explainable lightweight convolutional neural network with global–local context-enhanced channel attention for grape leaf disease detection," Computers and Electrical Engineering, vol. 128, Part B, p. 110745, 2025, doi: 10.1016/j.compeleceng.2025.110745.

[28] A. Aissaoui, I. Aloui, S. Boudibi, Z. -E. Khomri and A. Foughalia, "Deep Learning Approaches for Plant Diseases Identification and Classification: A Comprehensive Review," *2024 8th International Conference on Image and Signal Processing and their Applications (ISPA)*, Biskra, Algeria, 2024, pp. 1-11, doi: 10.1109/ISPA59904.2024.10536708.

29] S. Mondal, A. Ferraro, F. Pecorelli, M. Iammarino, and G. De Pietro, "Concept and rule guided neural network for early crop leaf nutrient deficiency diagnosis," Computers and Electronics in Agriculture, vol. 248, p. 111735, 2026, doi: 10.1016/j.compag.2026.111735.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[30] K. A. M. Han, N. Maneerat, K. Sepsirisuk and K. Hamamoto, "Banana Plant Nutrient Deficiencies Identification using Deep Learning," *2023 9th International Conference on Engineering, Applied Sciences, and Technology (ICEAST)*, Vientiane, Laos, 2023, pp. 5-9, doi: 10.1109/ICEAST58324.2023.10157689.

[31] Pacal, I., Kunduracioglu, I., Alma, M.H. *et al.* A systematic review of deep learning techniques for plant diseases. *Artif Intell Rev* **57**, 304 (2024). https://doi.org/10.1007/s10462-024-10944-7.

[32] İ. Avcı, M. Koca and Y. Z. Khan, "A Lightweight Mobile Deep Learning Framework for Real-Time Plant Disease Detection in Smart Agriculture," *2025 9th International Symposium on Innovative Approaches in Smart Technologies (ISAS)*, Gaziantep, Turkiye, 2025, pp. 1-9, doi: 10.1109/ISAS66241.2025.11101803.

[33] Shoaib M, Shah B, EI-Sappagh S, Ali A, Ullah A, Alenezi F, Gechev T, Hussain T and Ali F (2023) An advanced deep learning models-based plant disease detection: A review of recent research. Front. Plant Sci. 14:1158933. doi: 10.3389/fpls.2023.1158933.

[34] Sriram Ganesh, G., Praveen Kumar, K., Jaya Kumari, D., Kondreddi, L.N. (2025). Detecting Monkeypox Skin Lesions with Deep Learning: A Promising Approach for Early Diagnosis. In: Lin, F., Brigui, I., Kesswani, N., Mishra, M., Ray, A. (eds) Applications of Computational Intelligence in Management and Mathematics I. Springer Proceedings in Mathematics & Statistics, vol 492. Springer, Cham. https://doi.org/10.1007/978-3-031-84517-8_41

[35] J.-Y. Wu, Z. Y. Poh, A. C. Patil, B. Park, G. Volpe, and D. Urano, "Analysis of plant nutrient deficiencies using multi-spectral imaging and optimized segmentation model," arXiv preprint arXiv:2507.14013, 2025, doi: 10.48550/arXiv.2507.14013.

[36] L. Ale, A. Sheta, L. Li, Y. Wang, and N. Zhang, "Deep learning based plant disease detection for smart agriculture," in Proc. IEEE Globecom Workshops (GC Wkshps), Waikoloa, HI, USA, 2019, pp. 1–6, doi: 10.1109/GCWkshps45667.2019.9024439.